Job Lock: Evidence from a Regression Discontinuity Design

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Abstract

Employer-provided health insurance may restrict job mobility, resulting in "job lock." Previous research on job lock finds mixed results using several methodologies. We take a new approach to examine job-lock by exploiting the discontinuity created at age 65 through the qualification for Medicare. Using a novel procedure for identifying age in months from matched monthly CPS data and a relatively unexplored administration measure of job mobility, we compare job mobility among male workers in the months just prior to turning age 65 to job mobility in the months just after turning age 65. We find no evidence that job mobility increases at the age 65 threshold when Medicare eligibility starts. We also do not find evidence that other factors such as retirement, reduction in hours worked, social security eligibility, pension eligibility, and sample changes confound the results on job mobility in the month individuals turn 65.

Keywords: Job lock; health insurance; Medicare
JEL: J60, I13

1. Introduction

The predominant source of health insurance in the United States for working-age adults is employer-provided health insurance. Over three-quarters of full-time workers between the ages of 18 and 64 have health insurance through employers. In comparison, only 6 percent have health insurance purchased through the individual market and another 6 percent have public insurance (Fronstin 2010). A potential cost of this reliance on employer-provided health insurance is the non-portability of insurance across employers that potentially results in "job lock." Workers may be reluctant to leave their jobs to search for new ones when otherwise optimal because of the possible loss of coverage due to pre-existing condition exclusions, waiting periods on new jobs, loss of particular insurance plans, and disruption in the continuity of care with their healthcare providers.[1] Changing jobs during a health plan year may also result in the loss of any earned credit towards plan deductibles and unused balances in health reimbursement accounts. The heavily-debated Affordable Care Act (ACA) of 2010 attempts to increase coverage and portability of health insurance with key provisions coming into force in 2014.

Although the theoretical justifications for the existence of job lock are unambiguous, there is no consensus in the large and growing empirical literature on the size of job lock (Gruber and Madrian 2004). A number of studies find large and statistically significant estimates of job lock, often finding that health insurance reduces

1 Federal regulations (HIPAA and COBRA) aim to reduce these problems; however, individuals still have to either pay for potentially expensive continuation coverage if they terminate employment or face new pre-existing condition exclusions and waiting periods if they are uninsured for more than 63 days between jobs. COBRA is expensive with premiums averaged $4,824 for employee-only coverage and $13,375 for family coverage in 2009, and this expense may be responsible for low take-up rates of less than 10 percent (Fronstin, 2010). Take-up rates increased when legislation allowed for a temporary COBRA subsidy from 2009 to 2010, however, this subsidy has now expired (Bovbjerg et al. 2009).

job mobility by 25 to 50 percent (Cooper and Monheit, 1993; Madrian, 1994; Gruber and Madrian, 1994; Anderson, 1997; Stroupe, Kinney and Knieser, 2001, Adams, 2004; Bradley et al., 2007, 2012; Bansak and Raphael 2008; Rashad and Sarpong 2008; Tunceli et al., 2009; Boyle and Lahey, 2010). Other studies find no effects or smaller effects that in some cases attain statistical significance for specific demographic groups (Holtz-Eakin, 1994; Penrod, 1994, Slade, 1997; Kapur, 1998; Spaulding, 1997; Berger, Black and Scott, 2004; Dey and Flinn, 2005; Gilleskie and Lutz, 2002; Hamersma and Kim, 2009).

The existing literature generally employs one of three main identification strategies to estimate job lock. The most common approach taken in the previous literature is to use a difference-in-difference strategy that compares the probability of job mobility of otherwise similar employees who differ only in how much they value their current employer's health insurance policy.[2] Examples of measures of the demand for health insurance coverage used in the literature include pregnancy of spouse, family size, family health status, and availability of alternative health insurance coverage.[3] A second approach taken in the previous literature is to use changes in health insurance legislation through prices, taxes or expanded coverage as a natural experiment. For example, Gruber and Madrian (1994) use variation provided by continuation coverage mandates, Sanz Galdeano (2006) use the HIPAA reform, Bansak and Raphael (2008) use the implementation of SCHIP, Hamersma and Kim (2009) use Medicaid expansions, and

2 See Madrian (1994), Kapur (1998) and Bradley et al. (2007, 2012) for a few examples, and Gruber and Madrian (2004) for a review of the literature.
3 In their review of the literature, Gruber and Madrian (2004) discuss some concerns with this approach taken in many previous studies. A common measure of alternative health insurance coverage is spousal coverage, but this may be endogenous to the job mobility decision (Royalty and Abraham 2006). Other measures used to proxy health insurance demand are family health status and expected medical utilization. These may have relatively low power and/or be difficult to measure.

Boyle and Lahey (2010) use expansions of the VA health system to test whether better alternative coverage reduces job lock. Studies using this approach also find mixed results with magnitudes that vary depending on the sub-group and the reform studied. Finally, other studies have relied on structural models of job mobility and find somewhat smaller estimates of job lock (Dey and Flinn, 2005; Gilleskie and Lutz, 2002). Health insurance and job mobility are determined simultaneously in these models.

In this paper, we take a new approach to study the question of job lock. We exploit the abrupt change in health insurance coverage occurring at age 65 due to Medicare in a regression discontinuity design (RDD). The discontinuity in coverage suggests that a comparison of job mobility for workers just below the age 65 cutoff to those just above the age 65 cutoff provides a test of the job lock hypothesis that is as close to a random experiment as possible. For identification, the RDD relies on relatively weak assumptions compared with those required for the other non-experimental approaches previously taken in the job lock literature (Lee and Lemieux 2010). Indeed, as discussed below, individual characteristics are essentially identical just before and after the threshold, mimicking the typical comparison of treatment and control characteristics in a random experiment. Although previous studies exploit the discontinuity in health insurance coverage created by Medicare (e.g. Card et al. 2008, 2009), the approach has not been previously taken to identify the effects of health insurance coverage on job mobility.[4]

The lack of a previous study using this identification strategy to test the job lock hypothesis is likely due to the difficulty in finding a dataset that includes a high-

4 In other work, we use the approach to examine the effects of employer-based health insurance on business creation (Fairlie, Kapur and Gates 2011).

frequency measure of age, a measure of job mobility, and a large enough sample size to focus around age 65. To create the high-frequency measure of age, we use a novel procedure for identifying a person's age in months from matching the four consecutive months of data for each person in the Current Population Survey (CPS). We take advantage of a relatively unknown survey administration variable in the CPS that measures if an individual changes jobs from the previous survey month. The combination of fifteen years of matched monthly files from the CPS provides a large enough sample size to focus around the age 65 cutoff.

The RDD approach has one potential disadvantage in estimating job lock. The approach only provides a local estimate of job lock, and thus might not be generalizable to other age groups of workers. As a result, we would emphasize caution in generalizing our results to other groups of workers, or for that matter, comparing our estimates directly to those in the literature that have been estimated using all workers.

Although we are very cautious about generalizing results to other age groups, we provide evidence below that job mobility rates, the characteristics of job mobility, and the skill and industry composition of the workforce do not differ substantially for older workers compared to middle-age workers, and therefore there may be valuable lessons from studying this group. In any case, older workers represent a large and growing share of the labor force and are of interest on their own. Currently, there are 15 million male workers ages 55 and over, representing 20 percent of the total male labor force (Toosi 2009). In the next decade, the number of older workers is projected to grow to over 20 million. Labor force participation rates among older workers are high and are projected to increase over time for the oldest groups (see Figure 1). By 2018, 63 percent of male workers ages 60-64 and 40 percent of male workers ages 65-69 are projected to be in the labor force (Toosi 2009). Furthermore, the increase in the Social Security normal retirement age to 67 for those born after 1959 may result in more near-elderly workers balancing work and health insurance in the future. Recently, debates over the federal budget deficit have turned the discussion towards also increasing the Medicare eligibility age to 67 (Kaiser Family Foundation 2011). An understanding of the factors influencing work patterns and mobility will be critical to forecasting how the near elderly workforce in the United States will evolve in the coming years and respond to these policy changes.

2. Data

We use data from the 1996 to 2010 monthly Current Population Survey (CPS). This survey, conducted by the U.S. Census Bureau and the Bureau of Labor Statistics, is representative of the entire U.S. population and interviews more than 130,000 individuals in approximately 60,000 households per month. Households in the CPS are interviewed each month over a consecutive four-month period in each of two rotations starting one year apart. Our study uses a novel approach of matching individual-level monthly data from the CPS to create a 4-month panel data set. By matching consecutive months of the CPS, we can identify the month in which the person's age (in years) changes, which is defined as the birth month.[5,6] Since the CPS interviews households for 4 consecutive months, we can identify up to two months before the birth month, the birth month, and 2

5 To match these data, we use the household and individual identifiers provided by the CPS. False matches are removed by comparing race, sex and age codes from the two months. All non-unique matches are also removed from the dataset. Monthly match rates are generally between 94 and 96 percent, and false positive rates are very low. Match rates are even higher among older individuals.

6 Starting in August 2002, the Census Bureau “masked” the age variable for some respondents ages 65 and over in the CPS to protect confidentiality (U.S. Census Bureau 2010). We have confirmed that our results are not sensitive to this procedure. Details are available in the Online Appendix.

months after the birth month.[7] We cannot, however, identify the birth month of individuals whose birth month does not fall in the four month interview window. Few data sets contain a large enough sample size as well as information needed to identify exact birth month. The approach also has an advantage over previous RDD studies that rely on age in years or quarters because we do not have to make potentially strong assumptions about the shape of the relationship between age and the outcome. The effects of age on job mobility will be small because we can narrow the focus to only a couple of months before and after the age 65 birth-month cutoff.

To measure job mobility, we take advantage of an underutilized survey administration variable in the CPS that measures if an individual changed his/her job from the previous survey month. The CPS was redesigned in January 1994, and one of the design changes aimed to avoid unnecessary duplication in the questions asked of respondents. As part of this design change some questions referred back to the answers given in the previous month. The job change variable used in this study is derived from this "dependent interviewing" approach. If a respondent is reported employed in one month and is also reported employed in the previous month's survey, the interviewer asks the respondent whether they currently work for the same employer as reported in the previous month (the interviewer reads out the employer's name from the previous month to ensure accuracy). If the answer is yes, then the interviewer carries forward the industry, occupation and other job characteristics information from the previous month's survey. If the answer is no, then the respondent is asked the full series of industry,

7 As expected, we find that roughly 25 percent of the sample (3 out of 12 months in which we can observe an age change in the following month) experiences an age increase in the data. We also find very few cases in which age increases by more than one year or decreases over consecutive months. The high levels of accuracy are due to the CPS carrying forward age information for respondents based on recorded birth dates.

occupation, and other job questions. Using the answer to this routing question, we can identify job stayers (workers employed in two consecutive months at the same employer) and job changers (workers who changed employers between two consecutive months). The measure does not suffer from recall error associated with questions asking about retrospective information. This variable has been used in only a few previous studies, and none that have examined job lock.[8]

Job mobility rates are slightly understated in the matched CPS because of the relationship between geographical mobility and job changes, and the loss of observations in the matched CPS when a household moves. The understatement, however, is small. We find a job change rate of 1.74 percent for ages 60-69 for the matched CPS compared to 1.80 percent for ages 60-69 using the full cross-sectional CPS (using comparable work definitions). Also, we do not find evidence of a differential age profile for job change rates estimated from the two different samples. We have also investigated the possibility of changes in sample density around the age 65 cut-off, and found that this does not pose a problem.[9]

The main sample includes male workers who work 30 or more hours in a wage/salary job in the first survey month and have a wage/salary job in the second survey month in each consecutive 2-month survey pair.[10] We exclude women from the analysis because of labor force participation concerns. The use of data from the 1996 to 2010 CPS implies that the women who reach age 65 in the sample were born in the 1930s. This cohort of women has a low labor force participation rate. Our analysis design requires a

8 Other studies that have used this variable have examined the cyclicality of mobility and job hopping in Silicon Valley (Fallick, Fleischman and Rebitzer 2004, 2006; Mazumder, 2007; Nagypal 2008).
9 Detailed results are available in the Online Appendix.
10 This sample definition is consistent with the job lock literature. In practice, we find that the regression results are not sensitive to the choice of hours in either the first or second job.

large number of observations, and for women there were too few observations for a full-time worker sample around the age 65 cutoff. We also use the extensive information on demographic, job, and region characteristics available in the CPS, such as race, immigrant status, marital status, education, hours of work, industry, region and urbanicity of residence.[11] CPS sample weights are used throughout the analysis.

JOB MOBILITY RATES

Figure 2 plots job mobility rates by age for male wage/salary workers ages 25 to 70. Job mobility rates start out high for young workers, but decline rapidly with age over the next two decades. At age 25 more than 3 percent of workers change jobs each month. By age 35 the rate of job mobility drops to 2 percent and by age 45 the rate of job mobility drops to 1.5 percent. The likelihood of job mobility remains at this level for the remainder of the working career. Job mobility rates for workers in their 50s and 60s are in the same range as job mobility rates for workers in their mid-40s.

Focusing on older workers, an interesting finding is that job mobility rates do not change substantially from ages 55 to 70. There is no strong upward or downward pattern in job mobility around age 65, which makes it easier to identify changes at age 65. The finding that job mobility rates do not fluctuate substantially in the few years around age 65 suggests that we do not need to make strong assumptions about the age/job mobility profile. Figure 2 also does not provide evidence of a large increase in job mobility rates at age 65.

11 The monthly CPS data do not have employer-provided health insurance (EHI). We predicted EHI using demographic and job characteristics, and found that job lock for those with high predicted EHI was similar to the rates reported in the paper. Detailed results are available in an Online Appendix.

Before examining job mobility rates around the age 65 cutoff in more detail, we examine whether the characteristics of job change are different for older workers than for younger workers. Table 1 reports work characteristics of job changers by 5-year age groups. Among job movers, we find that 33.8 percent of job changers in the 60-64 age group report changing major industries, which does not differ substantially from the rate for middle-age workers. We also find that the average hours worked after the job change does not differ substantially by age group. We condition on full-time work in the initial survey month, but place no restrictions on hours worked in the subsequent survey month of the two-month panel. Older workers also have a similar rate of movement between government and non-government work as middle-age workers. Finally, older full-time, wage/salary workers have similar educational and industry distributions as middle-age workers.[12] Overall, the characteristics of job mobility and the characteristics of the workforce do not noticeably differ for older workers than for middle-age workers.

3. Age 65 Discontinuity

To examine the question of whether health insurance discourages job mobility we exploit the discontinuity created at age 65 through the qualification for Medicare. In the month that individuals turn 65, they automatically qualify for Medicare, providing access to free health insurance coverage for hospital care and heavily subsidized coverage for other medical services.[13] Medicare coverage is not subject to pre-existing condition exclusions or waiting periods, reducing concerns about job-lock. Attaining Medicare eligibility should immediately reduce the value an individual places on employer-

12 Results for the industry distribution are available in the Online Appendix.
13 Individuals automatically qualify for Medicare Part A (hospital insurance) in the month they turn age 65 if they have 40 quarters of previously covered employment or have a qualifying spouse. Medicare Part B (medical insurance) can be purchased for approximately $100 per month.

sponsored health insurance. Potential job changers no longer have to be concerned about losing health insurance coverage after that date.

Evidence that Medicare coverage increases substantially at age 65 is provided in Card et al. (2008). Using National Health Interview Survey data, they find that Medicare coverage jumps from 12.3 percent at age 63/64 to 72 percent at age 65. In addition, overall insurance coverage jumps from 87.9 percent at age 63/64 to 97.4 percent at age 65. Our analysis uses monthly CPS data which do not contain information on health insurance. While the March CPS data do contain health insurance information, using these data to analyze jumps in insurance at age 65 is problematic. March CPS data is collected annually, so, we cannot show changes in insurance status at the monthly level around the age 65 cut-off. Furthermore, insurance information gathered in the March CPS refers to coverage at any time during the previous calendar year. The age data is reported in March of the current year. There is also a concern that Medicare coverage is under-reported in the CPS (DeNavas-Walt et al., 2006). Despite these concerns, our descriptive analysis of the March CPS data shows that there is a sharp rise in Medicare coverage at 65. The percent reporting Medicare coverage jumps from 2.6% at age 64 to 53.3% at age 65 and then to 73.1% at age 66 (with age measured in March). For our sample of workers, Medicare rates at age 66 are lower than the virtually universal coverage that we may have expected, which is likely due to the question in the CPS asking "At any time in <year ????> were you covered by Medicare."[14] Workers who are covered by employer-based insurance may only report this coverage, even though they are eligible for Medicare as well. For the purposes of our estimation strategy, the fact that there is a large

14 Medicare eligibility is nearly universal since it is based on individuals having (or their spouse having) a minimum of 10 years of Medicare-eligible work history. Medicare eligibility can also be gained through disability; however there are no changes in this form of eligibility at age 65. Our sample of male workers should be more likely to meet the work-eligibility requirement than non-workers.

jump in Medicare eligibility at age 65 should be sufficient to provide the variation required to estimate job lock.[15]

Using the monthly CPS data, we can isolate the effects of the Medicare discontinuity by comparing job mobility rates just before the age 65 birth month to just after the age 65 birth month. Individuals qualify for Medicare on the first day of the month that they turn 65, and as noted above, matching consecutive months of the CPS allows us to identify the month in which they turn 65. Since this approach is tightly focused on the months before and after the 65 birth month, it addresses concerns over the potential influence of unobservables such as health insurance preferences and individual health status on the estimates.

We start by graphing job mobility rates in two-month intervals around age 65 (see Figure 3 using monthly CPS data). We choose a binwidth of two months to partly smooth the data for presentation. Plotting job mobility rates by one-month bins, which is the smallest possible bandwidth in the data, reveals a much noisier graph (see Appendix Figure 1). As noted above, the 4-month rotation of the CPS only allows us to identify months around the birth month, which is why the figures do not display job mobility rates for age in months in the middle of the birth year. From the plot of job mobility rates by age in two-month intervals we do not see evidence of an increase in job mobility starting at age 65. In fact, the job mobility rate appears to decrease for workers who are just under age 65 to workers who are just over age 65. Fitting simple linear regression lines to either side of the age 65 cutoff clarifies these patterns. We do not find evidence of an increase in job mobility rates after workers turn age 65.

15 In theory, a first stage model of the effect of age 65 on Medicare eligibility could be used to scale job lock estimates. However, we do not have data on Medicare eligibility. We also do not have a measure of the potential disruption caused by changes in health insurance providers and pre-existing condition exclusions or waiting periods. Thus, estimating a credible first-stage model for job lock is not possible with the data.

The estimates displayed in Figure 3 reveal another interesting pattern. Job mobility rates are relatively constant with the age of older workers. No clear upward or downward trend appears over the full age range. This finding is important because it lessens the potential for biases introduced by not accurately specifying the age-job mobility profile. The RDD results are thus likely to be insensitive to how we model the age function.

Examining trends in job mobility by age in two-month intervals does not reveal a break at age 65. We now examine job mobility rates by age in years. Although we cannot focus in as much on the age 65 discontinuity by using age in years as the bandwidth, we can increase precision substantially. By using age in years, we are able to add back the three quarters of the original sample in which we cannot identify the exact birth month in the four-month CPS rotation. Figure 4 displays the results using age in years for the bins for the analysis. These are the same data that are presented in Figure 2, but here we focus on ages 60-69 and show linear regression lines on either side of the break. Similar to the results using age in two-month intervals, there is no evidence of an increase in job mobility rates at age 65. From age 64 to age 65 there is actually a slight decline in job mobility rates, but generally there is no major change in job mobility rates over the age range. Linear regression lines on either side of the cutoff also do not reveal an increase in job mobility rates at age 65.

4. Regression Discontinuity Models

We now turn to a more formal regression analysis of the age 65 discontinuity. We follow the framework and recommendations presented in Lee and Lemieux (2010) and

Imbens and Lemieux (2008). We start by estimating a parametric regression for the probability of a job change. The linear model used as a starting point can be expressed as:

$$(4.1)\ Y_i = \alpha + \beta(A_i - c) + \tau W_i + \gamma(A_i - c)W_i + \varphi' Z_i + \varepsilon_i, \text{ where } c\text{-}h \le A_i \le c\text{+}h$$

where Y_i is an indicator for job change, h is the bandwidth, A_i is the individual's age in months, c is the cutoff (i.e. age 65), W_i=1 if the individual is age 65 or over, Z_i is a vector of additional covariates, and ε_i is the error term. The specification allows for a different slope of the age/job mobility function on either side of the age 65 cutoff. The parameter of interest is τ, which captures the change in the probability of job mobility at the age 65 threshold or the estimate of job lock.

Equation (4.1) is similar to a non-parametric, local linear regression, however, one possible concern is that the conditions for non-parametric methods are not technically satisfied in the discrete case (Lee and Card 2008). Our measure of the “forcing” or “running” variable, age in months is discrete, but as Lee and Lemieux (2010) note as long as the discrete variable is not too coarsely distributed the estimation strategy is similar. Thus, the main limitation created by our measure is that we cannot estimate local linear regressions with very small bandwidths. Choosing a bandwidth of two months, for example, would only provide two possible values for variation in the forcing variable on either side of the cutoff. Choosing a bandwidth of one month provides only one possible value on either side of the cutoff, and thus results in a simple comparison of means. Overall, however, the reduction in potential bias associated with using very narrow bandwidths is likely to be small because of the relative constancy of job mobility rates with age as displayed above. To create a large bias job mobility rates would have to change substantially over only a few months, which they do not appear to do. Additionally, information on exact birth dates could theoretically allow for smaller bandwidths, but these bandwidths (less than one month) are likely to produce very imprecise and highly variable estimates of job lock.

There are several features of the model that are advantageous in this setting. First, the forcing or running variable in the RDD, age, is immutable. Age cannot be altered to affect Medicare eligibility avoiding a potential problem with RDDs when the forcing variable can be manipulated by individuals or other participants to affect placement around the threshold. Second, the use of age in months decreases the binwidth relative to age in years, and thus improves the internal validity of the approach around the threshold. Third, the CPS allows us to control for a rich set of variables that are not typically available in administrative datasets. An examination of the sensitivity of job lock estimates after the inclusion of these controls and estimates of equation (4.1) using these variables as dependent variables provides further evidence on the internal validity of the RDD in this setting.

Estimates of equation (4.1) are reported in the first column of Table 2 for age ranges from 14 months to 62 months around the age 65 cutoff.[16] The reported bandwidths or age ranges correspond to the clusters of age in months identifiable in the matched CPS. Examining observations on the left side of the age 65 cutoff for example, the smallest bandwidth reported (14 months) includes the two identifiable months just prior to age 65

16 The sample includes workers with 30 or more hours worked per week in the initial survey month. Estimates are similar including workers with any hours worked (Appendix Table 1). Also, estimates are similar when restricting the sample to jobs with 20 or more hours worked per week or 40 or more hours worked per week.

and the five identifiable months clustered around age 64 (see Appendix Figure 1). Bandwidths are then increased by one-year increments to capture the next cluster of possible age in month values. For all bandwidth choices, we do not find evidence of an increase in job mobility rates from just under the cutoff to just over the cutoff. In fact, none of the point estimates using the different bandwidths are positive. Additionally, the coefficient estimates using the various bandwidths are similar to the simple mean change in job mobility rates from the month before turning age 65 to the month after turning age 65 (-0.0013) and the change in job mobility rates from the two-month average before turning age 65 to the two-month average after turning age 65 (-0.0107).

We also estimate the optimal bandwidth. Using the Imbens and Kalyanaraman (2012) technique we find an optimal bandwidth of 48 months. Using the Ludwig and Miller (2007) and Imbens and Lemieux (2008) technique we find that a bandwidth of 14 months minimizes the mean square of the differences, but the values are fairly similar across bandwidths. Instead of reporting only the optimal bandwidth identified by these techniques we continue to present several bandwidths (which also show that this choice does not influence the results).

We also estimate regressions using higher-order polynomials (i.e. quadratic, cubic and quartic specifications) for the job mobility - age relationship. The quadratic specification, for example, is expressed as:

(4.2) $Y_i = \alpha + \beta_1(A_i - c) + \beta_2(A_i - c)^2 + \tau W_i + \gamma_1(A_i - c)W_i + \gamma_2(A_i - c)^2 W_i + \varphi' Z_i + \varepsilon_i$, where $c\text{-}h \leq A_i \leq c+h$

The inclusion of a higher-order polynomial allows for a more flexible relationship between job mobility and age. Column 2 of Table 2 reports estimates of equation 4.2. We do not report specifications in which the order of the polynomial is smaller or the same size as the number of clusters of identifiable months otherwise the polynomial would effectively over-fit the data. An example of this problem would be estimating a quadratic specification in which we only have two clusters of identifiable months on either side of the cutoff. Estimates from the quadratic specification do not change our conclusion – none of the point estimates are positive. We do not find evidence that the probability of job mobility increases at age 65.

Table 2 also reports estimates for higher-order polynomials for the age-job mobility function. The estimates for the cubic and quartic specifications do not differ substantially from the quadratic estimates. Across all bandwidths, we do not find evidence that the probability of job mobility increases at age 65.

Specification tests along the lines suggested by Lee and Lemieux (2010) do not provide clear evidence favoring the use of higher-order polynomials over the linear specification. First, we add dummy variables for each possible age in month bin and jointly test their statistical significance. If the age bin dummies are jointly significant for a specific polynomial order then a higher-order polynomial might be needed to better fit the data. For 14-month and 26-month bandwidths, the age bin dummies are not statistically significant for the linear or higher-order specifications. For the longer bandwidths, the age bin dummies are generally significant for all polynomial orders. There is also no clear reduction in the significance level for the test when increasing the order of the polynomial. The only exception is for the 38-month bandwidth regression where moving from the quadratic specification to the cubic specification increases the p-value from 0.022 to 0.051 favoring the cubic specification. For the second test, we conduct an Akaike test of significance that induces a penalty for adding additional variables. The AIC values are very similar across the different polynomial orders and do not provide clear evidence favoring higher-order polynomials.

We do not find that the higher-order polynomials improve the explanatory power of the regressions over the linear specifications. The discontinuity estimates are also not sensitive to the choice of polynomial order. This lack of sensitivity is perhaps not surprising given that the simple plots of job mobility rates by age did not reveal a strong downward or upward pattern with age. We continue by discussing results primarily from linear specifications, but report estimates for higher-order polynomials and note any major differences.

The CPS allows for a rich set of controls to be included in the regressions. Appendix Table 2 reports the same set of specifications as reported in Table 2 after controlling for individual and job characteristics. We include controls for race, nativity, married, education, region, urbanicity, industry, and year fixed effects. The inclusion of these controls has little effect on the estimates. The lack of sensitivity of the estimates to the inclusion of covariates provides additional evidence on the validity of the regression discontinuity design.[17]

Using these estimates we examine whether we can rule out large positive effects on job mobility for our sample of older workers. Figure 5 displays regression discontinuity estimates for different bandwidths and their 95 percent confidence intervals

17 As expected given that the forcing variable is age, we do not find evidence that the covariates change at the age 65 cutoff (see Online Appendix for figures on college education and minority share). Additionally a simple comparison of means of the independent variables for observations just under age 65 and just over age 65 reveals that they are very similar.

from the linear specification. All of the point estimates are negative. For the 26-month bandwidth, we can rule out a positive job mobility effect. For three additional bandwidths, we can rule out large positive job mobility effects. These estimates rule out effects of 0.002 to 0.003, which represent 12 to 19 percent of the job mobility rate of 0.017 at age 64. It is important to note that previous studies in this literature have used annual or quarterly job mobility data, and as a result, the point estimates are on a different scale compared to our work that uses monthly job mobility. By dividing the point estimates by the average mobility rate, we can in effect, standardize the estimates across the possible analytic time frames.

Examining the 95 percent confidence intervals resulting from the higher-order polynomial specifications, we also find that we can rule out large job lock effects for older workers. In most cases, we can also rule out positive or small positive effects on job mobility. Using the quadratic specification, for example, we can rule out positive effects for two bandwidths and positive effects of 3 to 13 percent for the other two bandwidths. These results further support the conclusion that our estimates can rule out large job mobility effects for older workers.[18]

AGE IN YEARS

We estimate regressions using age in years as the forcing variable. As noted above, a major advantage of this approach is that we can use the full sample, which is four times larger than the sample in which we can identify age in months from the rotation pattern in the CPS. Table 3 reports estimates (Appendix Table 3 reports estimates

18 By constraining the slopes on either side of the age 65 threshold to be the same we can further improve the precision of our estimates. The constancy of job mobility rates by age suggests that constraining the slopes to be equal does not seem like an overly restrictive assumption. In many cases, 95 percent confidence intervals can rule out even larger effects.

with controls). Similar to the estimates using age in months as the forcing variable, we do not find evidence of a positive effect of turning age 65 on job mobility. All of the point estimates from the various bandwidths and polynomial orders are not positive and are very small. The coefficient estimates are also relatively similar across bandwidths and polynomial orders. We do not find evidence of a preference for using a higher-order polynomial to estimate the discontinuity.

Using the age in years specification we can rule out large, positive effects of job lock for older workers. Figure 6 displays estimates and their 95 percent confidence intervals from the linear specifications by bandwidth. All of the point estimates are negative and in this case their standard errors are precise enough that we can rule out the possibility of large positive effects. For two specifications the upper bound of the 95 percent confidence interval rules out effects larger than 10 percent of the mean job mobility rate. In two additional specifications, we can rule out estimates that are more than 15 percent of the job mobility rate. The largest upper bound can rule out positive effects that are more than 20 percent of the job mobility rate. Similar to the estimates measuring age in months we can rule out large positive job lock effects.

EXTENDING THE AGE RANGE

Because of the lack of substantial trends in job mobility over age, we extend the age range used in the sample. Table 4 reports estimates for bandwidths of 72 months to 122 months (roughly 6-10 years on either side of the cutoff).[19] For the linear specification the point estimate for job lock remains negative and small using the 72 month to 98

19 Appendix Table 4 reports estimates for bandwidths of 6-10 years using age in years as the forcing variable.

month bandwidths. The point estimates become positive, but very small for the 110 month and 122 month bandwidths. For the quadratic and higher-order polynomials the estimates do not differ substantially from the estimates using the smaller bandwidths. In all cases, the point estimates are negative and we can rule out large positive effects for older workers. The longer bandwidths provide more precision and allow us to rule out even smaller positive effects in many cases. Most of the estimates for the cubic and quartic specifications allow us to rule out any positive effects. For instance, for the quartic specification with band-widths of 98 - 122 months, the 95% confidence interval allows us to rule out the existence of any job lock for older workers.

5. Retirement, Social Security and Other Potentially Confounding Factors

RETIREMENT AND OTHER FACTORS

One concern is that the age of 65 may be associated with other labor force transitions. Other than changing jobs, individuals may retire or reduce their hours worked per week.[20] Figure 7 displays retirement hazard rates in two-month intervals around age 65. The dependent variable is whether the wage/salary worker with 30+ hours in the initial survey month retires by the subsequent survey month. There does not appear to be an increase in retirement at the age 65 cutoff although there is some noise in the displayed retirement hazard rates. Appendix Table 5 reports regression estimates for the retirement probability using different bandwidths and polynomial orders. The results paint a consistent story – there is no evidence of a statistically significant positive effect on retirement.[21] Although qualifying for Medicare at age 65 might reduce the influence of

20 Previous research provides evidence that health insurance costs reduce retirement rates (see Johnson et al., 2003 for example).

21 This finding also lessens concerns that Medicare-induced job mobility occurs through job to retirement to unretirement transitions that we would miss with the monthly job change measure available in the CPS.

employer based health insurance on retiring it may represent a small effect relative to loss of income. We also examine whether hours worked changes at the age 65 threshold, and find no evidence of a change. Results are in the Online Appendix.

OTHER POLICY CHANGES AT AGE 65

Another issue with the regression discontinuity estimates is that there might exist policy-related confounding factors that lead to shifts in employment behavior at age 65 such as eligibility for Social Security or pensions. However, Social Security eligibility does not appear to confound our analysis of job mobility precisely at age 65 for two main reasons. First, the earliest age of eligibility for Social Security benefits is 62; benefits received by individuals at that point are reduced (in an actuarial neutral way) relative to what would be received if one were to retire at the full retirement age. Administrative data on Social Security benefits reveal that individuals are far more likely to begin claiming benefits at age 62 than at age 65 (Munnell and Sass 2007). In 2004, 56 percent of eligible men elected to receive Social Security benefits starting at age 62 compared with 23 percent when they turned 65.

Second, while the full retirement age for full Social Security benefits was 65 for individuals born in 1937 or earlier (i.e., those reaching eligibility before 2003), Social Security reform enacted into law in 1983 increased the full retirement age by two-month increments per year of birth beginning with the 1938 birth cohort until it reached 66 for those born in 1943.[22] The cohorts affected by the reform reached their full retirement age

See Maestas (2010) for evidence of unretirement patterns among older workers.

22 For cohorts born between 1943 and 1954 the full retirement age remains at 66. For subsequent cohorts, the full retirement age will increase in 2 month increments until it reaches 67. However, these younger cohorts do not reach retirement age in our sample period (http://www.ssa.gov/retire2/retirechart.htm).

in 2003-2010, which is covered in our sample period.[23] For these cohorts, the propensity to claim Social Security exactly at age 65 has fallen dramatically because of the change in the full retirement age. For example, for the 1939 birth cohort with the full retirement age of 65 years and 4 months, almost 50 percent claimed Social Security at age 62, and about 16 percent claimed at 65 years and 4 months; however, there was no spike in the claiming rate at age 65 with only about 2-3 percent claiming in that month. Thus, the increase in the full retirement age further reduces the potential effect of the age 65 threshold on Social Security claiming behavior (Song and Manchester, 2007).[24]

Similarly, age 65 does not appear to be a primary focal point for the accrual or availability of pension wealth. Under defined contribution retirement plans, pension wealth accrual does not vary substantially by age; pension wealth continues to increase as long as a person works. The critical age for individuals covered under defined contribution plans is 59.5 because at that age individuals can begin withdrawing from a 401(k) without penalty (Friedberg and Webb, 2003). Under defined benefit plans, pension wealth accrual peaks at the age of early retirement eligibility, which is well before age 65. Pension wealth may continue to increase up to age 65 (Friedberg and Webb, 2003; Poterba, Venti and Weiss, 2001). In both the case of Social Security and pensions the evidence provided in previous studies does not indicate a major change in take-up at age 65.

CHANGES AT OTHER AGES

23 In 2000, Social Security eliminated the earnings test for claiming between ages 65 and 69. Empirically, the effect of the increase in the full retirement age dominates the elimination of the earnings test for cohorts that retire after 2003, and therefore, there is no increase in the Social Security claiming exactly at age 65 (Song and Manchester, 2007).

24 We find no evidence of job lock effects when we restrict the sample to cohorts born in 1938 or later, and thus do not receive full Social Security benefits at age 65.

We investigate whether there are any breaks in job mobility in other birth months. Investigating potential breaks at other ages provides a type of falsification test unless there is a different policy reason for the break. For example, eligibility for other social programs, such as Social Security, falls on birthdays or birth months, and there could be an independent "celebratory" birthday effect. Alternatively, if there was systematic miscoding in the age data, the age 65 effect may appear at a different birth year. To investigate this possibility, Table 5 reports estimates for job mobility regressions using all ages as cutoffs from age 60 to 70. Estimates from a linear specification with a bandwidth of 62 months are reported, but the findings are similar using a quadratic specification. The estimates do not indicate a statistically significant break at any age. Thus, we do not find evidence that job mobility increases discontinuously in any of the birth months when individuals turn ages 60 to 70.

6. Conclusions

A major concern with the U.S. focus on employer provided health insurance is that it might restrict job mobility. The potential loss or disruption in health insurance coverage due to pre-existing condition limitations, waiting periods for coverage, changes in health plans and providers, and risk of high health costs while uninsured may dissuade many employees from leaving their job to seek a new one when it would otherwise be optimal.

We take a new approach in the job lock literature by examining the discontinuity created at age 65 through the qualification for Medicare. We find no evidence of an increase in job mobility after workers become eligible for Medicare. None of the RDD estimates are positive. The upper bound of 95 percent confidence intervals for these estimates can also rule out the existence of any job lock in some cases, and in most cases can rule out large levels of job lock for our sample of older workers. These results are robust to different bandwidths, polynomial orders for the age function, annual vs. monthly age measurement, and inclusion of controls for detailed individual and worker characteristics. It is important to note that our estimates are based on older workers and our results may not be directly comparable to job lock estimates in the literature that apply to all workers.

In examining the possibility that other factors confound the results for job lock, we do not find any evidence that retirement, work hours, sample densities, demographics, or work characteristics change at age 65. There also is no evidence that other policies potentially affecting job mobility occur at age 65. Age 65 is considered the full retirement age for Social Security for cohorts in 1937 or earlier, but benefit eligibility starts at age 62 and benefit levels increase smoothly up to age 65. Furthermore, for cohorts born after 1937, the full retirement age for Social Security benefits is after the 65th birthday, reducing the probability of claiming Social Security at age 65.

The finding of no job lock for workers at age 65 suggests that employer provided health insurance does not substantially limit job mobility for older workers and possibly middle-aged workers. We find that older workers do not look markedly different than middle-aged workers with a large share remaining in the labor force and similar job mobility rates. The characteristics of job changes for older workers and overall labor force characteristics also do not differ substantially from middle-aged workers. Additionally, we might expect a priori, that older workers are more likely to be affected by job lock because of higher demand for health care. Average annual total health care expenditures for people ages 45 to 64 are $5,843 compared with $2,974 for people ages 18 to 44, and 89 percent of people ages 45 to 64 incur some expense. Over three-quarters of 45-64 year olds have one or more chronic condition (AHRQ 2008). But, even with a higher demand for health care among older workers further research is needed to determine if the results presented here can be extrapolated to other age groups.

Beyond the implications for the job lock literature, these findings are important for understanding the labor market decisions of a large and growing share of the labor force – the near-elderly. Workers ages 55 and over are projected to total more than 20 million by 2018. Increases in the Social Security normal retirement age to 67 and recently proposed increases in the Medicare eligibility age may result in an increased number of older workers balancing work and health insurance in the future.

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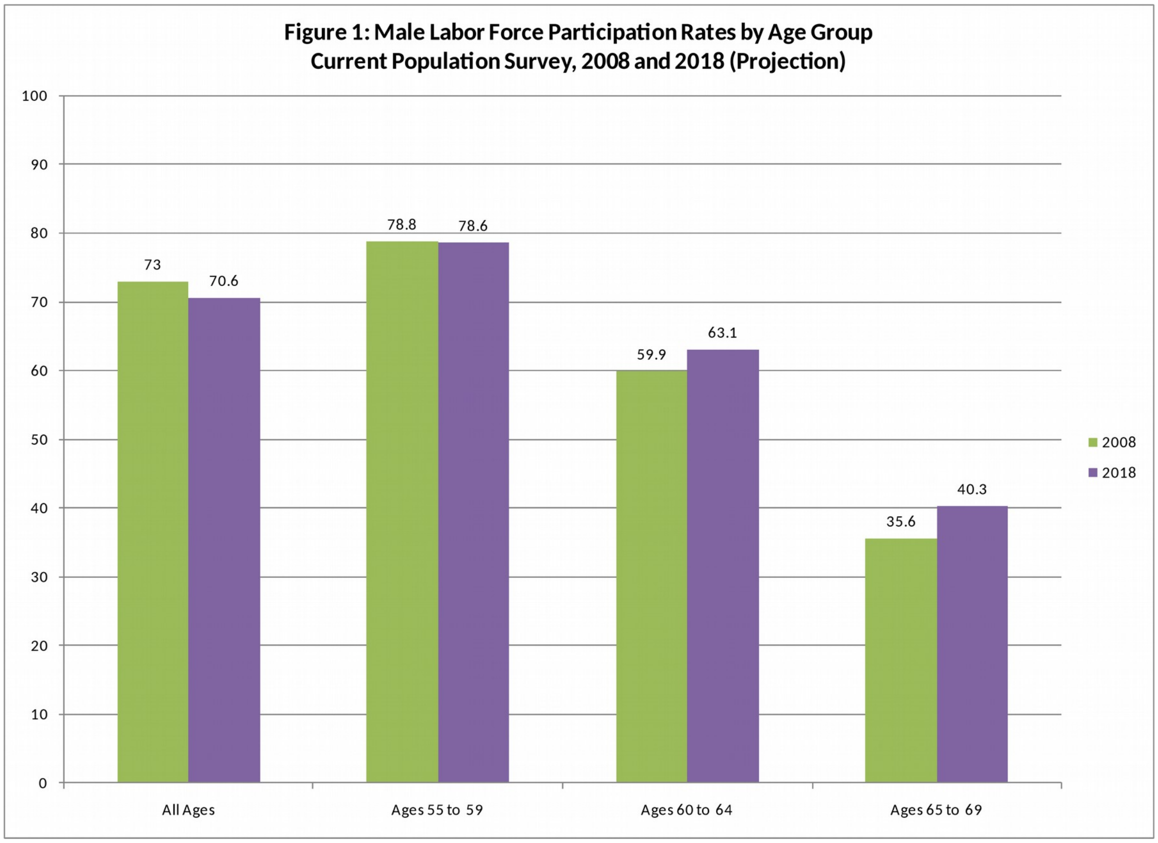


Source: Toosi (2009)

Figure 2: Monthly Job Mobility Rates by Age in Years for Male Wage and Salary Workers
Current Population Survey, 1996-2010

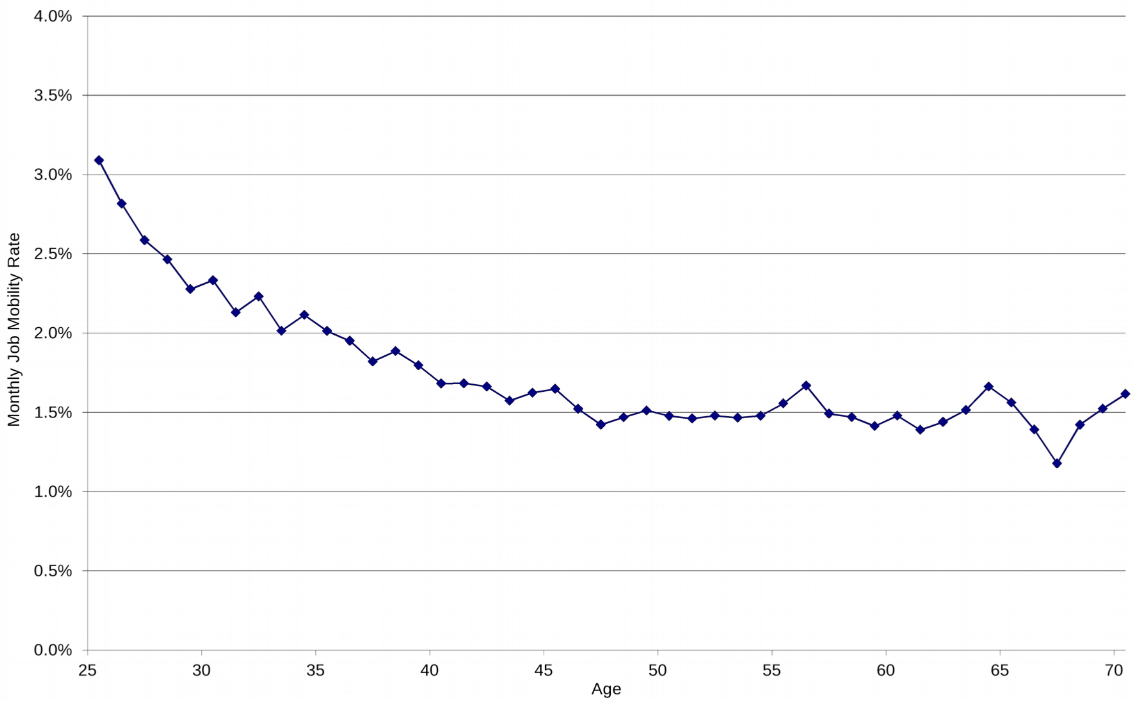


Figure 3: Job Mobility Rates by Age in 2-Month Intervals

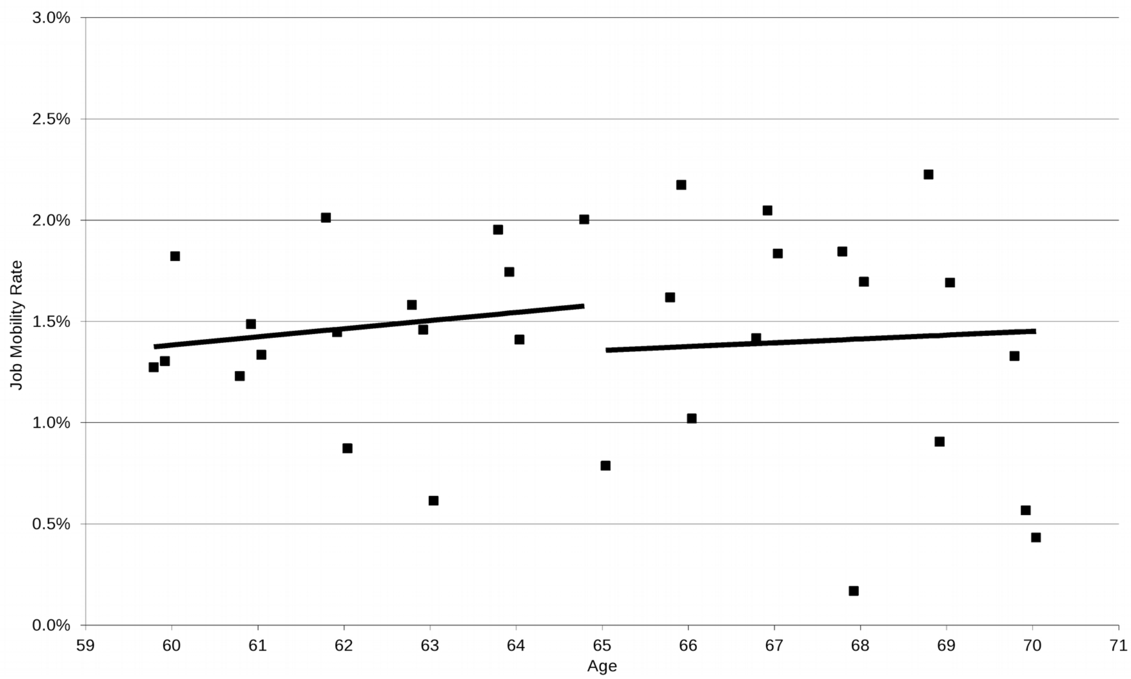


Figure 4: Job Mobility Rates by Age (Measured in Years)

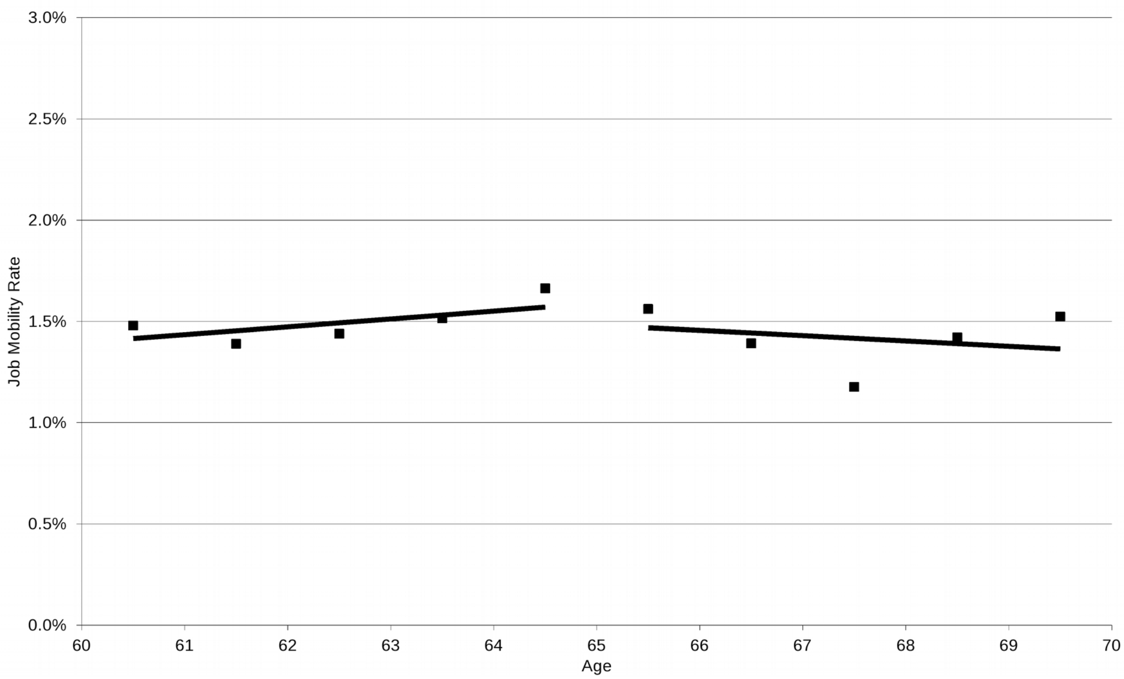


Figure 5: Confidence Interval for RDD Estimate of Job Lock by Bandwidth

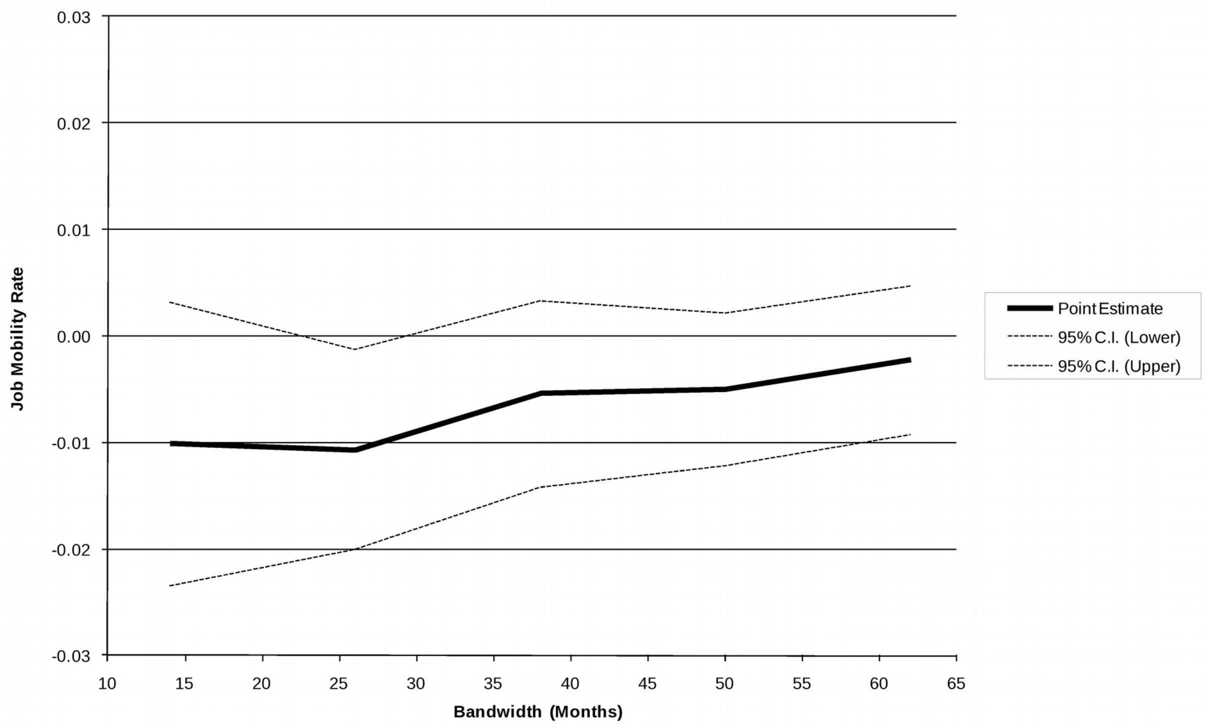


Figure 6: Confidence Interval for RDD Estimate of Job Lock by Bandwidth (Age in Years)

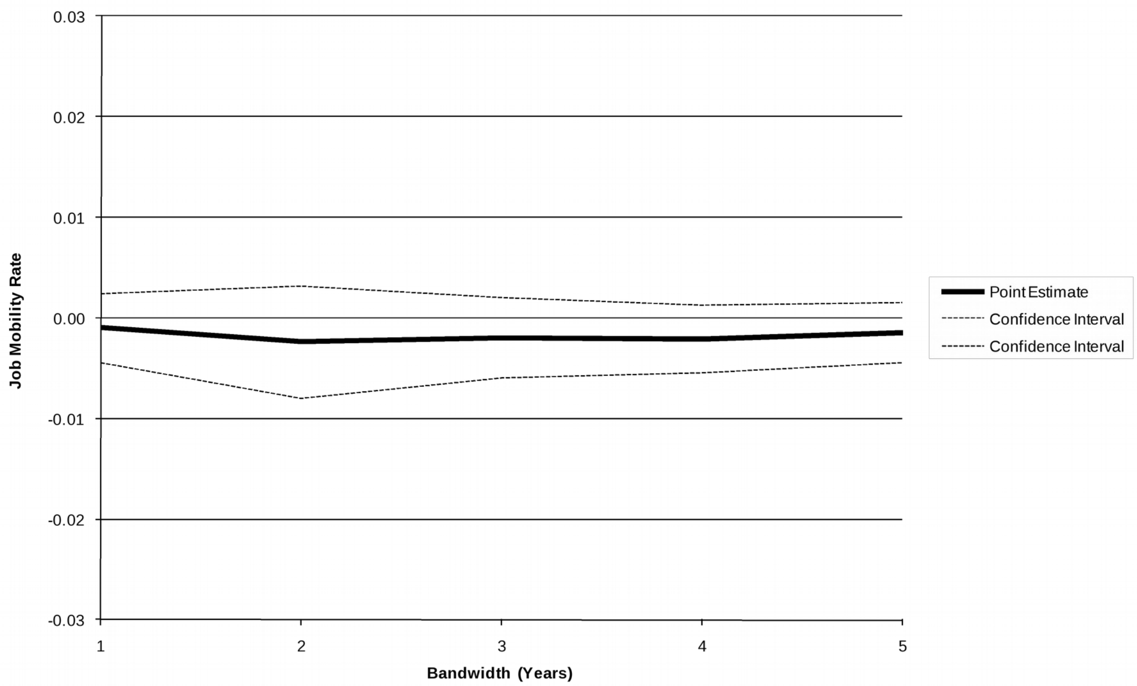


Figure 7: Retirement Rates by Age in 2-Month Intervals

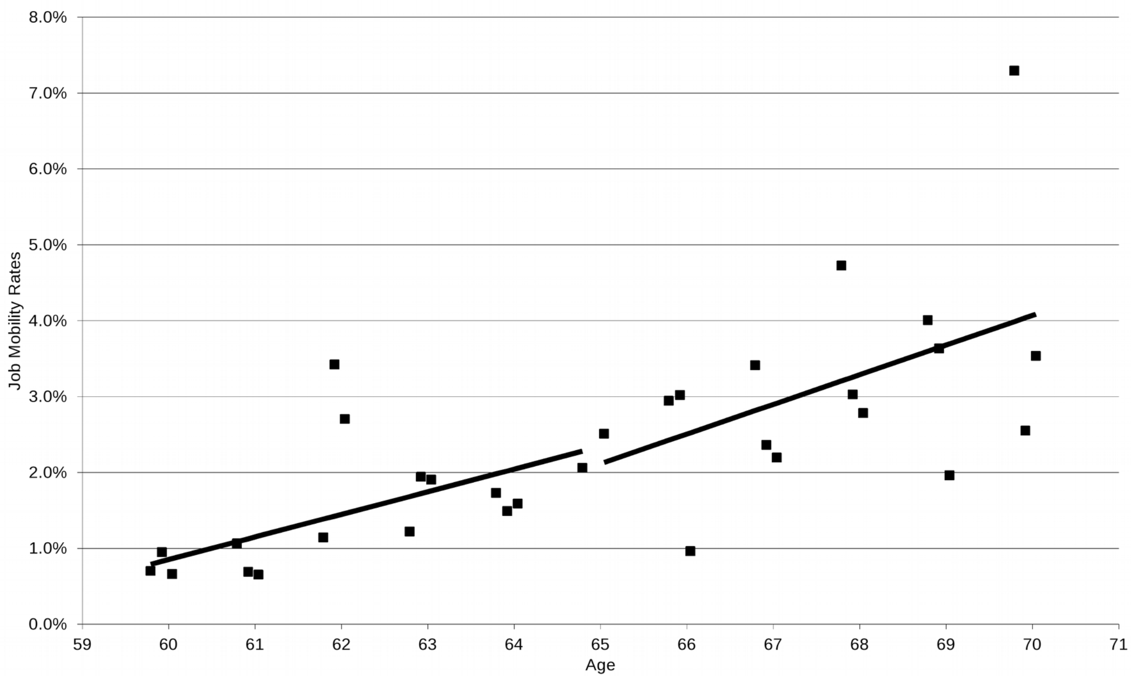


Table 1: Job Mobility Rates, Characteristics of Job Mobility, and Skill Composition of Workforce by Age Group (Ages 25-69)

	Ages 25-29	Ages 30-34	Ages 35-39	Ages 40-44	Ages 45-49	Ages 50-54	Ages 55-59	Ages 60-64	Ages 65-69
Job change rate	2.6%	2.2%	1.9%	1.7%	1.5%	1.5%	1.5%	1.5%	1.4%
Sample sizes	343,285	379,083	405,291	416,564	395,960	337,114	239,538	123,494	38,683
Job changers experiencing:									
Industry change	46.7%	42.6%	41.3%	39.3%	37.6%	35.6%	34.0%	33.8%	28.2%
Mean hours (t+1)	41.5	42.4	42.6	42.6	42.9	42.5	42.3	41.0	39.3
Government/non-govt. transition	6.7%	5.9%	5.6%	6.6%	7.1%	7.6%	7.3%	6.5%	8.4%
Sample sizes	9,096	8,137	7,540	6,761	5,959	4,943	3,600	1,840	566
Worker skills									
High school dropout	11.8%	11.4%	10.8%	10.0%	9.2%	9.2%	10.5%	13.0%	15.3%
High school graduate	31.3	30.3	31.7	32.4	31.0	29.5	29.2	29.3	28.3
Some college	27.7	26.1	25.5	25.9	26.8	26.7	25.2	22.9	20.9
College graduate	29.2	32.2	32.0	31.7	33.0	34.6	35.1	34.8	35.4
Sample sizes	343,285	379,083	405,291	416,564	395,960	337,114	239,538	123,494	38,683

Notes: (1) The sample includes male wage/salary workers with 30 or more hours worked per week in the initial survey month. (2) The job changer sample includes workers who also changed jobs from the initial survey month to the subsequent survey month.

Table 2

Regression Discontinuity Estimates of Age 65 on Job Mobility Rates

Bandwidth	Linear	Quadratic	Cubic	Quartic	N
14 Months	-0.0101				8,158
	(0.0068)				
26 Months	-0.0107	-0.0125			14,475
	(0.0048)	(0.0075)			
38 Months	-0.0055	-0.0155	-0.0078		22,570
	(0.0045)	(0.0066)	(0.0076)		
50 Months	-0.0050	-0.0103	-0.0152	-0.0080	31,738
	(0.0036)	(0.0055)	(0.0077)	(0.0079)	
62 Months	-0.0023	-0.0100	-0.0133	-0.0125	41,356
	(0.0035)	(0.0048)	(0.0066)	(0.0080)	

Notes: (1) The dependent variable is whether the worker changed jobs from the initial survey month to the subsequent survey month. (2) The sample includes workers with 30 or more hours worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in months are in parentheses below coefficient estimates. (4) No controls are included.

Table 3
Regression Discontinuity Estimates of Age 65 on Job Mobility Rates (Age Measured in Years)

Bandwidth	Linear	Quadratic	Cubic	Quartic	N
1 Year	-0.0010				26,839
	(0.0017)				
2 Years	-0.0025				54,282
	(0.0028)				
3 Years	-0.0019	-0.0032			84,708
	(0.0021)	(0.0049)			
4 Years	-0.0020	-0.0027	-0.0037		121,782
	(0.0017)	(0.0032)	(0.0086)		
5 Years	-0.0014	-0.0034	-0.0022	-0.0052	162,177
	(0.0015)	(0.0026)	(0.0051)	(0.0153)	

Notes: (1) The dependent variable is whether the worker changed jobs from the initial survey month to the subsequent survey month. (2) The sample includes workers with 30 or more hous worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in years are in parentheses below coefficient estimates. (4) No controls are included.

Table 4
Regression Discontinuity Estimates of Age 65 on Job Mobility Rates
Expanded Age Range (Ages 55-70)

Bandwidth	Linear	Quadratic	Cubic	Quartic	N
74 Months	-0.0006	-0.0092	-0.0118	-0.0143	51,747
	(0.0033)	(0.0043)	(0.0060)	(0.0075)	
86 Months	-0.0007	-0.0060	-0.0132	-0.0121	62,793
	(0.0031)	(0.0042)	(0.0055)	(0.0068)	
98 Months	-0.0007	-0.0046	-0.0113	-0.0143	74,794
	(0.0029)	(0.0041)	(0.0052)	(0.0066)	
110 Months	0.0007	-0.0051	-0.0083	-0.0152	88,244
	(0.0028)	(0.0038)	(0.0049)	(0.0062)	
122 Months	0.0009	-0.0043	-0.0083	-0.0131	92,934
	(0.0027)	(0.0038)	(0.0047)	(0.0059)	

Notes: (1) The dependent variable is whether the worker changed jobs from the initial survey month to the subsequent survey month. (2) The sample includes workers with 30 or more hours worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in months are in parentheses below coefficient estimates. (4) Controls include race, immigrant status, marital status, education, region, urbanicity, industry and year fixed effects.

Table 5

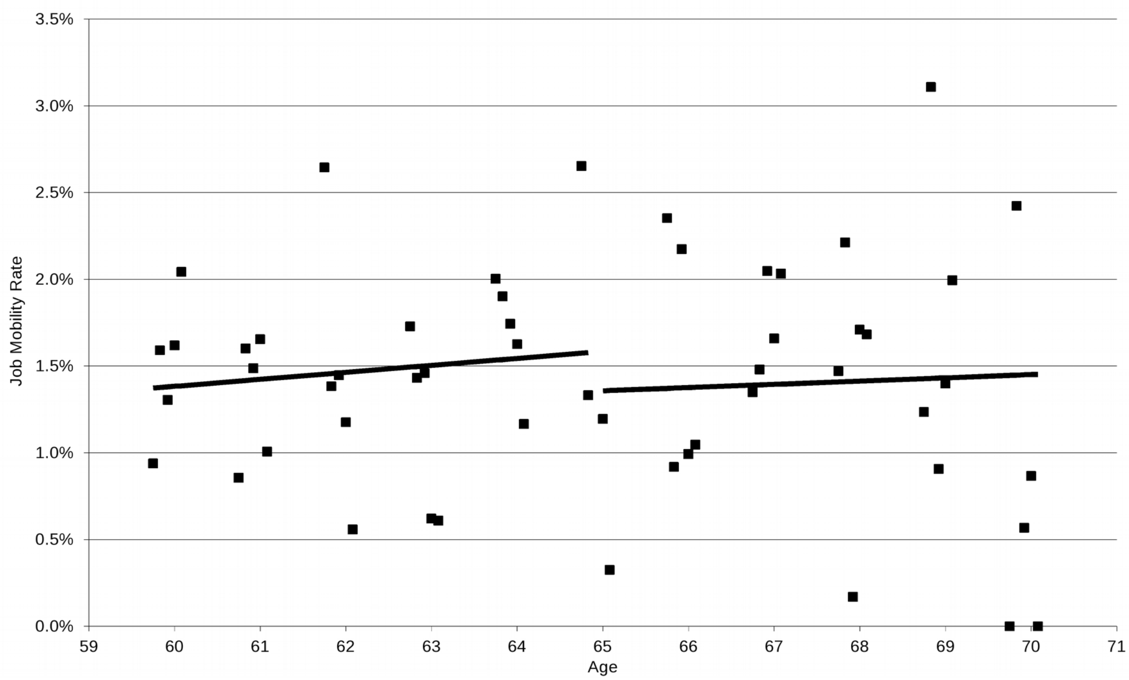
Regression Discontinuity Estimates for Job Mobility Rates at Different Age Cutoffs

	Linear Specification (Bandwidth=62 Months)			
Cutoff Age	Coefficient	Std. Err.	t-stat	N
60	0.0009	(0.0021)	0.44	82,043
61	0.0001	(0.0026)	0.04	80,036
62	-0.0042	(0.0026)	-1.63	69,050
63	-0.0014	(0.0032)	-0.45	59,459
64	0.0010	(0.0032)	0.31	50,205
65	-0.0023	(0.0035)	-0.65	41,356
66	0.0007	(0.0033)	0.22	33,442
67	0.0036	(0.0035)	1.01	25,961
68	-0.0024	(0.0035)	-0.67	19,706
69	-0.0038	(0.0041)	-0.91	15,436
70	-0.0070	(0.0045)	-1.55	11,919

Notes: (1) The dependent variable is whether the worker changed jobs from the initial survey month to the subsequent survey month. (2) The sample includes workers with 30 or more hours worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in months are in parentheses below coefficient estimates. (4) Controls include race, immigrant status, marital status, education, region, urbanicity, industry and year fixed effects.

Appendix Figures and Tables

Appendix Figure 1: Job Mobility Rates by Age in 1-Month Intervals



Appendix Table 1
Regression Discontinuity Estimates of Age 65 on Job Mobility Rates (Any Hours Worked)

Bandwidth	Linear	Quadratic	Cubic	Quartic	N
14 Months	-0.0091				10,643
	(0.0067)				
26 Months	-0.0058	-0.0113			18,765
	(0.0047)	(0.0075)			
38 Months	-0.0026	-0.0111	-0.0071		28,446
	(0.0041)	(0.0062)	(0.0077)		
50 Months	-0.0023	-0.0068	-0.0116	-0.0078	39,121
	(0.0032)	(0.0053)	(0.0073)	(0.0081)	
62 Months	-0.0017	-0.0053	-0.0103	-0.0100	50,122
	(0.0030)	(0.0047)	(0.0064)	(0.0078)	

Notes: (1) The dependent variable is whether the worker changed jobs from the initial survey month to the subsequent survey month. (2) The sample includes workers with 1 or more hours worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in months are in parentheses below coefficient estimates. (4) No controls are included.

Appendix Table 2
Regression Discontinuity Estimates of Age 65 on Job Mobility Rates with Controls

Bandwidth	Linear	Quadratic	Cubic	Quartic	N
14 Months	-0.0111				8,158
	(0.0070)				
26 Months	-0.0109	-0.0124			14,475
	(0.0050)	(0.0074)			
38 Months	-0.0054	-0.0155	-0.0077		22,570
	(0.0045)	(0.0067)	(0.0074)		
50 Months	-0.0051	-0.0104	-0.0152	-0.0081	31,738
	(0.0037)	(0.0055)	(0.0077)	(0.0078)	
62 Months	-0.0023	-0.0103	-0.0134	-0.0125	41,356
	(0.0035)	(0.0049)	(0.0065)	(0.0080)	

Notes: (1) The dependent variable is whether the worker changed jobs from the initial survey month to the subsequent survey month. (2) The sample includes workers with 30 or more hours worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in months are in parentheses below coefficient estimates. (4) Controls include race, immigrant status, marital status, education, region, urbanicity, industry and year fixed effects.

Appendix Table 3
Regression Discontinuity Estimates of Age 65 on Job Mobility Rates (Age Measured in Years) - Controls

Bandwidth	Linear	Quadratic	Cubic	Quartic	N
1 Year	-0.0010				26,839
	(0.0017)				
2 Years	-0.0024				54,282
	(0.0028)				
3 Years	-0.0020	-0.0032			84,708
	(0.0021)	(0.0049)			
4 Years	-0.0021	-0.0026	-0.0035		121,782
	(0.0017)	(0.0032)	(0.0086)		
5 Years	-0.0015	-0.0033	-0.0020	-0.0052	162,177
	(0.0015)	(0.0026)	(0.0051)	(0.0153)	

Notes: (1) The dependent variable is whether the worker changed jobs from the initial survey month to the subsequent survey month. (2) The sample includes workers with 30 or more hous worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in years are in parentheses below coefficient estimates. (4) Controls include race, immigrant status, marital status, education, region, urbanicity, industry and year fixed effects.

Appendix Table 4
Regression Discontinuity Estimates of Age 65 on Job Mobility Rates (Age Measured in Years)
Expanded Age Range (Ages 55-74)

Bandwidth	Linear	Quadratic	Cubic	Quartic	N
6 Years	-0.0016	-0.0022	-0.0044	0.0004	205,666
	(0.0014)	(0.0022)	(0.0039)	(0.0084)	
7 Years	-0.0015	-0.0021	-0.0032	-0.0047	252,409
	(0.0013)	(0.0020)	(0.0032)	(0.0060)	
8 Years	-0.0011	-0.0022	-0.0027	-0.0042	302,470
	(0.0012)	(0.0018)	(0.0028)	(0.0048)	
9 Years	0.0001	-0.0032	-0.0015	-0.0048	357,038
	(0.0011)	(0.0017)	(0.0025)	(0.0040)	
10 Years	0.0003	-0.0024	-0.0032	-0.0012	415,994
	(0.0011)	(0.0016)	(0.0023)	(0.0035)	

Notes: (1) The dependent variable is whether the worker changed jobs from the initial survey month to the subsequent survey month. (2) The sample includes workers with 30 or more hous worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in years are in parentheses below coefficient estimates. (4) Controls include race, immigrant status, marital status, education, region, urbanicity, industry and year fixed effects.

Appendix Table 5
Regression Discontinuity Estimates of Age 65 on Retirement Rates

Bandwidth	Linear	Quadratic	Cubic	Quartic	N
14 Months	0.0070				8,466
	(0.0057)				
26 Months	0.0047	0.0066			15,025
	(0.0052)	(0.0057)			
38 Months	0.0052	0.0072	0.0020		23,484
	(0.0058)	(0.0058)	(0.0062)		
50 Months	0.0005	0.0097	0.0059	-0.0003	32,910
	(0.0047)	(0.0072)	(0.0057)	(0.0067)	
62 Months	-0.0019	0.0068	0.0112	0.0011	42,822
	(0.0048)	(0.0060)	(0.0065)	(0.0061)	

Notes: (1) The dependent variable is whether the worker retired between the initial survey month and the subsequent survey month. (2) The sample includes workers with 30 or more hours worked per week in the initial survey month. (3) Robust standard errors adjusting for clustering by age in months are in parentheses below coefficient estimates. (4) Controls include race, immigrant status, marital status, education, region, urbanicity, industry and year fixed effects.